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The Impact of Gold Price and Us Dollar Index: The Volatile Case of Shanghai Stock Exchange and Bombay Stock Exchange During the Crisis of Covid-19

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Abstract

This literature aims to analyze the impact of the Dollar Index and Gold Price returns and volatility on stock market volatility of India and China, viz., Shanghai Stock Exchange and Bombay Stock Exchange Sensex, during the period of Covid-19. This study employs daily time-series data from January up to August for 2019, 2020, and a merged data of 2019-2020, i.e., Pre-Pandemic, Mid-Pandemic and Pre through Mid-Pandemic periods, respectively; to avoid possible abnormalities and heteroscedasticity, the GARCH (1,1) model is utilized to scrutinize the data depending on which distribution is more acceptable, GED or Gaussian, which is decided based on the Unit-Root and normality test results. The findings of this study prove that Gold Price mostly does have a significant effect on both markets, especially during times of financial crisis like the Covid-19 epidemic. Whereas Dollar Index has a significant impact on emerging markets such as India and China though significant effects persist in some cases, it is not valid in most cases.

Keywords: BSESN; COVID-19; DXY; GARCH; Gold; Spillover; SSE; Volatility

1. INTRODUCTION

On December 31st, 2019, a type of Pneumonia of an unknown cause was detected in Wuhan, China. Soon after which the Chinese government first reported to the WHO Country Office in China about the newfound infection. This lung-related issue was later on identified as a cause of a new coronavirus. After a month of observation, uncertainty, and rapid rate of escalation of the infection, this outbreak was declared a Public Health Emergency of International Concern on January 30th, 2020. On February 11th, 2020, The World Health Organisation (WHO) announced a name for the new coronavirus disease, naming it COVID-19, as the world later started addressing the disease as the same (WHO, 2020).

The outbreak of the Coronavirus; Covid-19, which will be referred to as C19 for the sake of this study, was a sudden and unexpected plague that struck the world, and in a way, set a halt to the daily and usual activities of mankind. Since the world was rapidly progressing and millions of new inventions and activities took place globally, the sudden pause of all literal and virtual movement did bring about many setbacks, as one would probably assume. This pandemic, of course, encompassed an effect on many, if not most, of the businesses in the world, which in turn caused the volatile fluctuations in stocks and financial markets. The Novel Coronavirus (COVID-19) spread from a territorial emergency in China's Hubei Province to a worldwide pandemic, values plunged, and market instability soared upwards around the globe (Terry, Scott R, et al., 2020). Various Global Financial organizations and platforms have stated that the current (May 2020) C19 situation will have significant effects on the world economy, so much that it will even exceed the 2007/2008 world economic crisis. This recent C19 has affected all financial markets globally; to be more specific, the share prices trend has fallen significantly and consistently (Bhattacharya et al., 2021). Studies uncovered that C19 significantly affected the money-related markets around the world. Definite signs of the effect of the C19 on the monetary markets have been seen in various money-related markets on the planet (A. N. Sansa, 2020). Stock market returns are known to respond to major events. Existing studies have identified several major events that have affected such returns, for example, disasters, sports, news, and environmental and political events (Al-Awadhi et al., 2020). According to Al-Awadhi et al. (2020), it is also known that stock market returns have reacted to endemic diseases, like the SARS outbreak and EVD breakout in the past. Due to the effect on the various equity markets, this paper aims to analyze how the Bombay Stock Exchange (BSE) and the Shanghai Stock Exchange (SSE) have been affected by Gold Price and US Dollar Index volatility. However, before this study was finished, a few experiments were undertaken after the COVID-19 outbreak to calculate stock market uncertainty compared to other capital markets. (Baker et al., 2020) just looked at how COVID-19 affects US stock market uncertainty. The study was carried out in the same way as (N. A. Sansa, 2020), with the confirmed cases of COVID-19 serving as independent data and China and US stock returns serving as contingent data. As a result, this study aims to determine the relationship between each variable before and during COVID-19 spreads by measuring stock market volatility as proxied by the BSE and SSE market using reference from the US dollar index and gold price in a period of one year (2019 to 2020).

Gold is a mineral, a chemical compound with the atomic number 79, and is found in the periodic table with the symbol Au (Latin: 'aurum') (Robiyanto, 2018). Gold is used in various fashions in today's world, i.e., jewelry, hedge fund, dentistry, risk diversifier, inflation predictor, etc. In the world of finance, gold is primarily used for its store of value abilities and its negative correlation with the American dollar, which makes it useful for hedging (Dyhrberg, 2016). Corbet, Larkin, & Lucey (2020) observed that the correlation between Chinese markets and gold grew to +0.335 and +0.347, respectively, with the Shanghai and Shenzhen stock exchanges COVID-19 was recorded to be negative. In regards to the US Petrodollar, China's market benchmark, the Shanghai Composite Index, has ascended around 10 percent from February to March or 2020, without being affected by the fact that demonstrated the production and administration segment's movements decreased strongly in February because of the effect of the coronavirus episode. The Yuan's exchange rate has additionally increased 0.73 percent against the US dollar, pulling back significantly from the key psychological line of 7.00, and making it the subsequently best performing among 11 significant Asian currencies (Karen Yueng; South China Morning Post 2020).

The US Dollar Index is a measure of the currency of the United States, i.e., the United States Dollar or USD, against a basket of countries weighed and used by the US trade partners. The DXY, USDX, and Dollar Index will fall if the dollar weakens against these countries and vice-versa (Marotta, 2015). The Dollar Index's main partners are weighed against are; EUR, JPY, GBP, CAD, SEK, and CHF. Although the SEK (Swedish Krona) is growing weaker, the weighted basket might be revised soon. The US Dollar Index, which is measured as a value of the United States currency against a number of its trade partners' currencies, strengthens when the value of the USD increases compared to other countries, hence, leading it to be a good benchmark for the value of the USD and a crucial measure for commodities that whose prices are dominated by the dollar (Sun et al., 2016). A study was conducted by (Lien et al., 2020) regarding the Dollar Index, US Stock market, and currency exchange on the Taiwanese stock market during the previous era of the financial crisis. This study found that the foreign exchange rate drastically affects the stock markets of both US and Taiwan. Fundamentally this means that Dollar Index does not have any direct impact on the stock markets. However, because the most significant influence on the stock markets was the exchange rates, it shows that the Dollar Index significantly influences the stock markets, especially the stock markets of Taiwan. The US Dollar Index indicates the strength or weakness of the dollar and is also an indicator to measure the exchange rate of the dollars in foreign exchange markets internationally. Since most internationally traded commodities are priced in dollars, the FOREX rate is highly significant and influential for the US Dollar Index.

On a global scale, India has the highest saving rate of approximately 30%, out of which 10% is invested in gold. Aruga & Kannan (2020) stated that based on the observation during the previous economic crisis of 2008, gold is linked to the financial crisis because of its sharp increase in investments. Empirical studies have found a strong correlation between the exchange rate and gold prices (Bombay Stock Exchange). On March 13th, 2020, in the early hours of trading around the time of 10 AM, the Indian stock markets crashed, and trading had to be paused for 45 minutes; The BSE Sensex touched a 10% lower circuit limit by dropping 3,090.62 points, reaching a low of 29,687.52 points, i.e., 9.43 percent (Raksit, Katare, et al., 2020).

Though previous studies are proving the volatility of the stock markets concerning Gold and US Dollar in BSE and SSE during such global epidemics, there is still a place to learn how policymakers could predict the expected share market path during an earlier period, before the condition matures and also to predict the moves of market participants based on the level of volatility (Gormsen & Koijen, 2020). There is also a gap in this field where analysis can be made by observing the first two quarters' market shock and find methods to keep investors interested by altering a more favorable interest rate (Baker et al., 2020). This study is going to contribute by emphasizing the impact of C19 on the stock market index such as Gold Price and USD against Indian Rupees and Chinese Yuan, in BSE and SSE respectively, before the strike of the widespread disease and the index volatility during the shock of the first quarter of 2020. In the current pandemic scenario, the economy is hesitant, and the stock system is unsure, posing a significant challenge. As a result, this study is intended to assist investors and traders in further understanding the factors that influence stock market volatility and provide additional insight on the impact of volatility on stock market price during pandemics, allowing them to make more informed decisions investment decisions and minimize danger. This study will be helpful to policymakers and will enable them to better understand the variables that influence stock market volatility.

Aside from that, the aim of this analysis is to prepare the next researchers to perform the next study.

2. HYPOTHESIS DEVELOPMENT

COVID-19

The COVID-19 pandemic has prompted a massive projection in unpredictability. Though the health authorities have conducted extensive research, reports indicate that the virus seems to react differently depending on the person infected. Medical facilities are going through vigorous challenges as the number of affected seemed to increase every day in most countries. It has been proven that infrastructures are not prepared for such a catastrophe. Though there are claims from political leaders about the development and deployment of vaccines, it is yet not verified how long that could take and by that time how much will the shock in terms of mortality rate. However, according to various news media, since the end of May 2020, many governments have initiated lockdown easing to support the general population's economies and anxiety. The initiation of the 'new normal' movement was being drafted to lead a daily life even in a crisis. This situation would allow the public to conduct almost all daily activities while observing the safety norms, such as physical distancing, avoidance of touching one's face, wearing safety masks in public, maintaining a hygienic and healthy lifestyle, etc. Nevertheless, the duration and effectiveness of the alleviations mentioned above and containment strategies together with the lockdown of markets, the economic impact and policy responses, along with the diminishing speed of the recovery of the pandemic, cannot promise for how long the temporary interventions of the government can last (Terry et al., 2020). It was stated by Scott R. Baker et al. (2020) that; given the fact that the invisible hand of the government is temporary, it is unlikely to predict: the consumer spending pattern which has been affected by the pandemic, the effect on business survival, formations of start-ups, development and research, capital investment and any other aspects that will have an impact on a short term or long term productivity, although as of now all the factors as mentioned earlier seem to be curving negatively.

The long-term consequence of the functioning economy coming to a standstill, on supply chains and financial organizations, the commercial sector, and the household economy, in general, is largely uncertain. Due to this, the business, policymakers, and stock traders are trying to calculate the approximate growth for years to come (Gormsen & Koijen, 2020). For example, the COVID-19 crisis leads to massive cuts in business expenditures on innovation, training, and general management improvements, which we expect to lower productivity into 2021 and beyond. Through various stock market volatility measures, it is a fact that the global epidemic has caused an extreme situation of uncertainty shock – this can be compared to the immensity of uncertainty caused in the years 1929 through 1933 during the era of the Great Depression (Baker et al., 2020).

Bombay Stock Exchange Index (BSE SENSEX)

The Bombay Stock Trade is represented and benchmarked by the S&P BSE SENSEX. The only other significant indices of India is the CNX Nifty, which means the National Stock Exchange. According to the S&P Dow Jones Indices, the S&P BSE SENSEX was launched on January 10th, 1986. India's most tracked trendsetter of an index is the S&P BSE SENSEX. It is designed to measure the 30 largest, most liquid, and financially sound companies across key sectors of the Indian economy listed at BSE Ltd. It is intended to quantify the functioning of the 30 biggest, generally fluid, and monetarily solid organizations across key parts of the Indian economy that are recorded at BSE Ltd (*S&P BSE SENSEX*, 2020).

Prior to COVID-19, the market capitalization of each of India's leading exchanges was about $2.16 trillion. Within the big caps, the 2019 stock market rebound was restricted to 8-10 stocks. For the year 2019, Sensex returned about 14% (excluding dividends), but it was dominated by blue-chip companies (HDFC Bank, HDFC, TCS, Infosys, Reliance, etc.), without which the Sensex would have returned negative returns. At the beginning of 2020, nearly 30 firms were scheduled to file initial public offerings (IPOs) at the start of the year. Business conditions were relatively favorable, with new highs being reached in mid-January (Bora & Basistha, 2021). However, on March 13th, 2020, the market had recovered to the point that both the NSE and the BSE were trading at their highest levels ever, with highs of 12,362 and 42,273, respectively. In the early hours of trading, around the time of 10 AM, the Indian stock markets crashed, and trading had to be paused for 45 minutes; The BSE Sensex touched a 10% lower circuit limit by dropping 3,090.62 points, reaching a low of 29,687.52 points, i.e., 9.43 percent (Katare et al., 2020).

Macroeconomic variables such as Gold and Exchange rate have been shown to have a substantial impact on the Indian Stock market. However, limited studies analyze the relation between BSE volatility and macroeconomic variables during the COVID-19. A Granger causality test showed a negative impact by Gold prices and Exchange rate on the Indian Stock market (Misra, 2018). Bilal et al. (2013) found a long-term relationship between average gold prices and BSE stock indices by using Co-Integrated Test. A study in 2012, cited Misra (2018), showed that out of most of the macroeconomic variables such as CRR, reverse repo rate, gold price, and FOREX, it was seen that gold price and FOREX, along with WPI and inflation, were the most significant. Polisetty et al. (2016) found no cause or effect of a meaningful relationship between stock price and FOREX in India. The study found that the degree of positive correlation is meager. However, there is a relationship between the two indices, i.e., FOREX and BSE. This relationship is "chance" rather than "cause"; due to the sensitivity of the Indian stock markets.

Shanghai Stock Exchange Index (SSE Composite)

The Shanghai Composite Index showed resilience to the COVID-19 pandemic with a significant gain in stock values during the first fifty days into the pandemic; on the contrary, the Dow Jones Industrial Average experience adverse impact from the COVID-19 pandemic with a significant loss of stock market value on its index during the first fifty days into the COVID-19 pandemic. Although the difference in stock values during the COVID-19 pandemic for Euronext 100 and the S&P 500 was not statistically significant, their mean stock index values show a reduction in value during the sample period first fifty days within the COVID-19 pandemic. From the initial results from various studies, it can be seen that the Chinese Composite Index showed resilience to the COVID-19 pandemic. The Chinese markets offer some degree of resiliency compared to other global stock markets (Ngwakwe, 2020). In the early 18th century, around the 1920s, with the founding of the Shanghai Chinese Securities Exchange, Shanghai emerged as the financial center of the Far East, of which both Chinese and foreign investors could trade futures, bonds, and stocks. In 1946, the Shanghai Chinese Security Exchange was renamed the Shanghai Securities Exchange Co., Ltd (Fulop, 2007).

Many types of research were conducted to discuss the relation between SSE volatility and macroeconomic variables (i.e., gold price and DXY). However, only a few of them are related to the COVID-19 pandemic, while they only analyze the impact COVID-19 period on the SSE return. The study conducted by G.G. Tian et al. found that the Chinese Yuan (RMB) against the foreign exchange rate of the US Dollar (USD) can cause stock prices to become cointegrated (Tian & Ma, 2010). This study found that the exchange rate of RMB against the USD affected the stock prices with a positive correlation, where, 1% change in the rate of the Chinese Yuan against the US Dollar would cause a 32% change in the long run of the SSE index. It was found by (Hoang et al., 2015) that the traders in Shanghai Gold Exchange and Shanghai Stock Exchange prefer portfolios with gold and without depending on whether they are risk-opposed investors or risk-seeking ones, respectively. The study also suggested that SGE would be considered in the diversification of Chinese stock and bond portfolios, especially during the crisis era. While during the COVID-19 pandemic, In the financial market context, the impact of COVID-19 is depicted in the first two months of 2020. Capital markets materialized the increased uncertainty regarding given a new pandemic by leading to the financial market volatility of Shanghai (-10%), Shenzhen (-6%), and Hong Kong (-19%) are down by comparatively modest percentages this year (Ruiz Estrada et al., 2020).

Stock Market Volatility

The definition of volatility in the context of this study is the unpredictability and unreliability of the changes in stock price within short-term periods. It can also be known as return volatility. In a stock market, if there is an elevated level of price volatility during periods of unstable trading, it may lead to a stock market crisis. It may also start affecting other markets (Rashid Sabri, 2004). The stock exchange market aids in the flow of excess funds, especially from those with surplus to those in deficit or from lenders to savers (Olweny & Omondi, 2011). Due to this reason, the emergence of volatility in stock markets has always been a substantial concern and affair for analysts and policymakers. When investors look for the potential market to trade in, it is commonly known and advised to check the volatility statistics of interested stock market returns. Quite a few traders prefer stocks that are highly volatile even though the chances of risks are high. This is due to the fact that stocks with high volatility level also have a high probability of achieving greater capital gains (Robiyanto *et al.*, 2018). Volatility can also be used and is used consistently to strengthen the accuracy of forecasting and the power of prediction. Nirodha I et al. (2015) stated in their study that for policymakers, a volatile stock market can be and will be a major concern because the uncertainty of stocks leads to instability and adversely impacts growth prospects. A study conducted by Handayani *et al.* (2018) analyzed the variables that affect stock market volatility. The variables used in the study to measure the significance of volatility were: Return on Equity, Cash Ratio, Debt Equity Ratio, Dividend Pay-out Ratio, company size, and sales growth. The study found that higher stock volatility is led by higher sales growth and that it was the only variable with a significant positive effect on stock price volatility.

The Corona-Virus-SARS-19 pandemic has had a significant impact on stock market volatility. It is common for high volatility to be correlated with economic and political vulnerability. There is proof of a positive effect on the Dow and Jones, and S&P returns (Onali, 2020). The high level of uncertainty of traders towards the C19 situation has caused and will cause even more considerable volatility of stock returns (Liu, 2020). A study conducted on the previous financial crisis era (2008) verified that financial catastrophes are instrumental to elevated stock return volatilities across major markets. The literature proved that the bigger a stock market, the greater the immensity of that market's persisting volatility (Karunanayake et al., 2009). Another study regarding the pre-crisis, mid-crisis, and the post-crisis era of the financial turmoil during 2008 observed that the stock market volatility of the S&P 500 Index increased to 43.6% from 13.4% in the mid-crisis period from the post-crisis-period respectively, and even after the markets rebounded and rallied from the crisis-era to the post-crisis era the volatility levels did not relapse the pre-crisis era levels, thus indicating that the traders and investors still believed and expected higher rates of market volatility despite the recovery (Fiszeder & Perczak, 2016).

Gold and Stock Market Volatility

Gold is a long-lasting and valuable metal that can be preserved and recovered at any time while maintaining its integrity. It is a chemical element with a high atomic number (79), and it is also known in the periodic table as Aurum (Au). Since gold is regarded as a precious metal, it is traded in the futures and commodities markets as bullion or gold bars of different weights (usually grams and kilograms) or as a monetary asset (Robiyanto, 2018).

Being that precious metals are traded in commodity markets, they have attracted the international attention of investors as a "safe haven" and as a substitute investment with a greater sense of positivity during chaotic periods. Not at all times is gold to be thought of as a safe haven for stocks. It is explicitly known for negative market shocks as the attribute of a safe haven is short-lived. Research conducted regarding gold as a hedge or safe haven stated; that gold is only a safe haven when it is most needed and is not supposed to be, nor is, so during periods of rising stock markets. The study by Baur & Lucey (2010) proved that though gold is a safe haven for stocks, in the long run, gold is definitely not a safe haven, as in the study states that hedge is described by Baur & Lucey (2010) as an asset that is uncorrelated (weak hedge) or negatively correlated (strong hedge) with some other asset owned by the investors on average. This study is also supported by (Dar & Maitra, 2017).

China will soon be a significant gold consumer, according to the World Gold Council (in 2015, the WGC stated that) (Hoang et al., 2015). A 30% drop in the Shanghai Stock Exchange (SSE) in 2015 resulted in a halt of trading for half of the listed companies to prevent further losses. When the stock market had a problem, the media frequently played up the myth of gold's inviolability. On average, gold is not a hedge, though it is a highly reliable safe haven under extreme stock market conditions during the same time periods in most Chinese stock markets (Ming et al., 2020).

Gold is traded on the Stock Exchange (Kumar & Gupta, 2019). With its unique socio-cultural status, India is the world's primary gold consumer. For emerging markets such as India, Gold is a weak safe haven at best. Looking at the peaks of certain crisis periods, gold is a strong and safe haven for most developed markets, while gold plays only a minor role in emerging markets against stock prices (Baur & McDermott, 2010). Gold is bought to prevent stock market declines and to counter inflation (Aruga & Kannan, 2020).

During the COVID-19 pandemic, most commodities in the market were disrupted, much like the stock and foreign exchange markets. According to Senol & Zeren (2020), the global primary product price declined by 37.3 percent in March 2020. However, it also reported that the precious metals sector increased by 5% during that period. The research studied by A. N. Sansa (2020) revealed that the positive correlation between Shanghai Financial Stock Markets and the COVID-19 confirmed cases is significant. I was having a significant positive relationship and impacting the stock markets of China. In the Q1 of

2020, regarding China's case, its retail sales and fixed assets dropped by 19.0 percent (year-over-year) and 16.1 percent, respectively (A. N. Sansa, 2020). This had led the economy of China to shrink by 6.8 percent in Q1 of 2020.

The case was 'Gold and Stock Correlation Under Uncertainty,' in which Gao & Zhang (2016) demonstrated that for the first time investors, when economic uncertainty increases, the shares for stocks drops drastically and demand remains constant, resulting in lower-risk/higher-quality assets pushing investors to divest their stock holdings and allocate them to 'flight to gold' Assets, such as gold and stock react inversely; this significantly impacts both volatilities (Lu et al., 2014).

H_{1a}: Gold Price has a positive effect on SHANGHAI Stock Exchange volatility

H_{1b}: Gold Price has a positive effect on BOMBAY Stock Exchange volatility

USD Index and Stock Market Volatility

The U.S. stock market is seen as the global information center, and any changes in U.S. stocks influence the volatility of stock markets worldwide, with an impact on foreign exchange markets (E.-D. Su & Fen, 2011). Wu and Wu (2017) mentioned the relationship between the US dollar and capital market participants in their study. The literature showed that the relationship between the carry trade aggregate returns and the USDX 5 futures prices appears to be more dissenting and continues in relation to the 2007-08 international financial crisis and the 2010-11 sovereign debt crisis of Europe, though the dollar index shows an ambiguous relationship before 2008. This special circumstance can be interpreted as a fact that when universal risk disinclination becomes high, global financial traders seem to redirect capital to a more balanced currency, during which the US Dollar inflates simultaneously. A strong positive symmetric volatility is USDX, implying that the investors turned to the US Dollar as a safe-haven instrument while the other currencies depreciated.

Hosen (2013) found that there is a significant influence of the US Dollar Index on the Jakarta Composite Index, i.e., if the USD Index increases, JCI would decrease. From the perspective of an investor, if the currency declines, it shows that the condition of the economy is not doing that well; as a preventive measure, the investors will be instigated to either invest less in the capital market or liberate their stocks, wherefore prompting the stock market (JCI) to experience a decline.

The Dollar Index significantly influences the Hong Kong stock markets, the fact being that changes in exchange rate greatly influence the Hong Kong stock returns volatility. The US dollar index, though not directly, plays a crucial role in the Hong Kong stock market since the exchange rate of Hong Kong is highly affected by the dollar index (Dai, Zhou & Dong 2020). Considering the circumstances of the stock market crash and high volatility, the DXY acts as a worthy haven for DAX, BSE, and NIKKEI225, while it is an unreliable one for SSE, SP500, and even BTC (Cheema & Szulczuk, 2020).

Demand for liquidity is known to increase in times of extreme market crisis. In such situations, the flight-to-liquidity paradox comes into effect, in which the preferences of traders change, and the price of illiquid assets drops, and the liquidity conditions of markets start to take a downturn (Ben-Rephael, 2017). The international flow of capital plays a significant role in defining the correlation between stock returns and currencies (in this case, USD), as they are a hedge trigger in flight-to-quality conditions. Due to this, investors from developing countries move towards investing in developed currencies as a natural haven, especially if a sudden crisis were to occur (Cho et al., 2016). Ghosh (2014) studied over a period of a pre-crisis and post-crisis era of the Indian markets and analyzed significant volatility spillover from the Indian stock markets and other financial market segments to foreign exchange markets. The Dollar index has been proven to have spillover effects from various stocks but should be invested in depending on the time as it is a high risk and high return index. According to J. Bin Su (2016), investing in the Dollar index pre-QE (Quantitative Easing) can lead to higher returns, whereas investing in the Dollar index can lead to a lower expectancy in post QE periods.

H_{2a}: US Dollar Index Negatively Impacts the SHANGHAI Stock Exchange Volatility

H_{2b}: US Dollar Index Negatively Impacts the BOMBAY Stock Exchange Volatility

3. METHOD, DATA, AND ANALYSIS

This study aims to analyze and prove the hypothesized theories by explaining and scrutinizing the data of the dependent and independent variables. The results will show how the dependent and independent variables correlate to each other. Four separate variables are being examined here: Gold price, US dollar index, and volatility in Shanghai and Bombay. The later variables (GOLD PRICE and the U.S. DOLLAR INDEX/INDEX/INDEX) are the independent variables. Quantitative (secondary) data were obtained from Yahoo Finance (beginning on June 17th, 2019, and spanning a total of one year, up to June 16th, 2020). Therefore, after the crisis, the degree of instability has been measured six months after Covid-19 and carries on until the middle of 2020, which constitutes a period of survival during the pandemic.

Operational Variables Defined

The study uses two dependent and two independent variables. The dependent variables are SSE stock return volatility and BSE stock return volatility, while the independent variables are Gold Price and US Dollar Index volatility. All the variables are collected and will be calculated on a daily basis.

The formula used to determine stock returns to calculate the volatility is as follows equation 1.

$$R_{SSE_{(t)}} = \left[\frac{SSE_{(t)} - SSE_{(t-1)}}{SSE_{(t-1)}}\right] \tag{1}$$

Where $R_{SSE_{(t)}}$ represents the SSE stock return on a particular day more inclined to the most recent day (t-day), $SSE_{(t)}$ is the symbol of SSE closing price on the t-day, and $SSE_{(t-1)}$ is SSE one day before the t-day. The same formula is also used to derive the stock return volatility of BSE SENSEX, as follows in equation 2.

$$R_{BSE_{(t)}} = \left[\frac{BSE_{(t)} - BSE_{(t-1)}}{BSE_{(t-1)}}\right] \tag{2}$$

The Dollar Index, which is an independent variable, will be determined by using the returns of the DXY index, which will be represented as $\Delta DXY_{(t)}$And can be calculated using the following equation 3.

$$\Delta DXY_{(t)} = \left[\frac{DXY_{(t)} - DXY_{(t-1)}}{DXY_{(t-1)}}\right] \tag{3}$$

In which, $DXY_{(t)}$ is the symbol used for the Dollar Index (DX-Y-NYB) on the t-day, and the day before the t-day is symbolized by $DXY_{(t-1)}$.

The gold price variable will be calculated using gold price changes which will be symbolized as $\Delta Gold_{(t)}$And can be gained using this equation 4.

$$\Delta Gold_{(t)} = \left[\frac{Gold_{(t)} - Gold_{(t-1)}}{Gold_{(t-1)}}\right] \tag{4}$$

Where $Gold_{(t)}$ represents the gold price at t-day, and $Gold_{(t-1)}$ is the gold price the day before the t-day.

The technique of Volatility Analysis

This research uses volatility as a dependent variable; therefore, it follows the GARCH (Generalized Autoregressive Conditional Heteroscedasticity Method). The GARCH models can account for heteroscedasticity, and nonstationary data is applied frequently in finance research connected to stock market returns (Putra & Robiyanto, 2019).

The application of the ARCH and GARCH models to empirical studies has exploded in their investigation of the market volatility in Malaysia, and the authors note that it emphasizes the non-binary clustering of attraction and overly-tailed return distribution. Estimation of the mean and conditional variance is built into the GARCH model

Conditional volatility is used to scrutinize the return of the market. If each variable studied has a conditional variance, the GARCH can be used (Hoga, 2019). The GARCH method consists of three steps: Normality check, Arch effect, and G-Based Estimator (Robiyanto, 2018).

The GARCH is presented as fluctuating over time (Hoga, 2019). The study will have two GARCH models since it has two dependent variables. Thus, the model is defined in equations 5 and 6.

$$V_{BSE} = \beta_0 + \beta_1 Gold_t + \beta_2 DXY_t + \sigma_t^2 + \varepsilon_t \tag{5}$$

$$V_{SSE} = \beta_0 + \beta_1 Gold_t + \beta_2 DXY_t + \sigma_t^2 + \varepsilon_t \tag{6}$$

Where:
$V_{BSE} = BombayStockExchangeReturns$
$V_{SSE} = ShanghaiStockExchangeReturns$
$\beta_1 \quad = GoldPriceReturns$
$\beta_2 \quad = USDollarIndexReturns$

With:

$$\varepsilon_t = \phi_1 \varepsilon_{t-1} + \eta_{t-p}$$

$$\eta_{t-p} = \sigma_t \in_t$$

With:

$$\sigma_t^2 = \alpha_0 + \sum_{i-1}^{q} \alpha_i e_{t-1}^2 + \sum_{j-1}^{p} \beta_j \sigma_{t-j}^2$$

$\alpha_i e_{t-1}^2$: Volatility of ARCH component
$\beta_j \sigma_{t-j}^2$: Volatility of GARCH component
The Error Term (ε_t) is independent and identically distributed N (0, 1), and independent from (η_{t-p}).

4. RESULTS

Descriptive Statistics

A descriptive statistic is used to calculate mean, standard deviation, minimum, maximum, and the amount of the data used. As stated in table 1, the data used in the pre-pandemic data is 83 data from January 2019 through August 2019. The gold return had the higher average in the pre-pandemic, which means that it had the highest return compare to the other variables. However, the gold return was considered to have an increased risk since the standard deviation value is 0.007461 and was highly volatile as the gold volatility average is 1.471483 (the highest average compared to the other volatility variables). In contrast, DXY return had the least standard deviation value (0.003022), which translates to DXY returns to have had the least risk compared to the other return variables. Though its return rate is considered low since the average of DXY returns was 0.45% (0.000451).

During the midst of this COVID-19 pandemic, DXY has shown a decline in their return (BSESN return: -0.24 percent, SSE return: -0.14 percent, DXY return: -0.05 percent). Besides that, BSESN return also had the highest standard deviation (0.028076), which means that apart from experiencing a decline during the COVID-19 pandemic, BSESN return is shown to have the highest risk. Additionally, gold had a positive value of average during the pandemic, which is 0.26% (0.002562) with a risk as much as 1.43% (standard deviation: 0.014352) and the least volatile compared to the other variables as the gold volatility average is 0.990003.

The total amount of data (both pre-and pandemic) used will be set at 164. As shown in table 1 from 2019 through 2020, the average of BSESN return (-0.14% or -0.001425), SSE return (-0.05% or -0.000495), and DXY return (-0.001% or -0.000014) are negative which means their returns were declined. Other than that, DXY has the lowest risk since it has a standard deviation of 0.004265, and BSESN has the highest since it has a standard deviation of 0.020471 compared to the others. Given the figures in the table, it can be seen that the gold return was the only one that had a positive average and the standard deviation of 1.15%, meaning that by 2019, there is a 1.15% risk and the least volatile compare to the other variables since the gold volatility average is 0.997445.

Table 1. Descriptive Statistics

Period	Variable	N	Minimum	Maximum	Mean	Std. Dev.
Pre-Pandemic (2019)	BSESN return	83	-0.015851	0.017358	0.0000102	0.007272
	SSE return	83	-0.024297	0.023856	0.000603	0.009339
	Gold return	83	-0.015345	0.035921	0.000864	0.007461
	DXY return	83	-0.008385	0.008258	0.000451	0.003022
	BSESN volatility	83	0.641952	1.751215	1.283853	0.251144
	SSE volatility	83	0.431807	1.165326	0.818626	0.208831
	Gold volatility	83	0.346959	2.803659	1.471483	0.656947
	DXY volatility	83	0.788329	1.406069	0.990913	0.137283
Mid-Pandemic (2020)	BSESN return	83	-0.131526	0.089749	-0.002398	0.028076
	SSE return	83	-0.077245	0.031464	-0.001351	0.017391
	Gold return	83	-0.04631	0.042512	0.002562	0.014352
	DXY return	83	-0.016131	0.015817	-0.000541	0.005182
	BSESN volatility	83	0.681364	1.096829	1.000892	0.087698
	SSE volatility	83	0.20774	4.967101	1.000219	0.682712
	Gold volatility	83	0.004803	7.331017	0.990003	0.817402
	DXY volatility	83	0.562803	1.145803	1.006415	0.138106
Pre-&-Through Pandemic (2019-2020)	BSESN return	164	-0.131526	0.089749	-0.001425	0.020471
	SSE return	164	-0.077245	0.031464	-0.000495	0.013923
	Gold return	164	-0.04631	0.042512	0.001638	0.011481
	DXY return	164	-0.016131	0.015817	-0.000014	0.004265
	BSESN volatility	164	0.688224	1.066968	1.001214	0.061493
	SSE volatility	164	0.300854	2.833198	1.000439	0.259216
	Gold volatility	164	0.076778	3.701894	0.997445	0.334265
	DXY volatility	164	0.604186	1.090616	1.002355	0.104963

Stationarity Test

The analysis of this study begins with a stationary test; the stationary test is used to comprehend whether or not there exists the presence of unit root in the data used, i.e., the returns of Bombay Stock Exchange (BSESN), Shanghai Stock Exchange (SSE), Gold Price Index (GC) and Dollar Index (DXY). To perform the unit-root test, the method executed for the investigation is the ADF Test or the Augmented-Dickey Fuller test, where the critical value (α) is 0.05 (5%).

It is to be noted that the data is accepted if the Probability is lower than the critical value (Probability <α). The data of returns used to conduct the ADF Test consists of three periods; 2019, 2020, and combined data of 2019 through 2020. This is because the study's main emphasis is on the volatility of the respective indexes and their relation pre and mid C19 pandemic. As shown in Table 2, the results of the ADF test verifies that the Probability for all of the data is below the critical value 0.05 hence proving that all the variables are stationary and hence accepted to be further scrutinized.

***Table* 2.** Stationary Test to find Unit-Root

Period	Variable	t-statistic	Probability
Before Pandemic 2019	BSESN	-9.0893	0.0000***
	SSE	-8.53556	0.0000***
	DXY	-10.3906	0.0000***
	GC	-9.94439	0.0000***
During Pandemic 2020	BSESN	-3.54396	0.0092***
	SSE	-8.69094	0.0000***
	DXY	-8.34472	0.0000***
	GC	-7.16376	0.0000***
January to August 2019 & 2020	BSESN	-3.54396	0.0092***
	SSE	-8.69094	0.0000***
	DXY	-8.34472	0.0000***
	GC	-7.16376	0.0000***

Note: *, **, *** indicates the level of significance at 10%, 5%, 1%

Normality Test

They are advancing from the stationary test the data is further scrutinized by performing a normality test. The normality test is performed to pronounce what model of GARCH is to be implied to scrutinize the derived data.

The GARCH equation has been used since its foundation by Tim Bollerslev (1986) in thousands of studies. The equation relies on three main models, i.e., Normal, Student-t, GED, or Generalized Error Distribution. Yaya et al. (2014) explain that while using the GARCH equation the scrutinize time-series data, it is common for Normal Distribution to be applied. However, the fact remains that most GARCH methods have a greater kurtosis than the normal distribution, which led to instate that the Normal (Gaussian) distribution is unacceptable for apprehending the tail performance of series. Hence, depending on the normality test, this study will use the GED distribution proposed by Nelson (1991), where the distribution of data is not normal.

The data will determine whether it is normally distributed or not depending on the results derived through the Jarque-Bera test. With the results originated through the normality test, it will be concluded on what GARCH model is best suited to obtain the empirical outcome. The data will be assumed normally distributed if the Probability is greater than the significance level, i.e., 0.05 (5%). In the case of high kurtosis, where the Probability is lower than 0.05, data is considered to be abnormal. Thus, for the deduction, the normally distributed data will use the Gaussian Model of GARCH, as for abnormal data, the Generalized Error Distribution or GED Model is applied. The results of the normality test can be observed in table 3.

Table 3. Normality Test

Pre-Pandemic Normality Test (2019)	Probability	Model
BSESN Returns to GC, and DXY returns	0.461946	Gaussian
SSE Returns to GC & DXY Returns	0.666606	Gaussian
BSESN Returns to GC and DXY Volatility	0.403898	Gaussian
SSE Returns to GC & DXY Volatility	0.401332	Gaussian
BSESN Volatility to DXY & GC Returns	0.399701	Gaussian
SSE Volatility to DXY & GC Returns	0.023229	GED
BSESN Volatility to DXY & GC Volatility	0.632085	Gaussian
SSE Volatility to DXY & GC Volatility	0.004931	GED
Mid-Pandemic Normality Test (2020)	**Probability**	**Model**
BSESN Returns to GC and DXY returns	0.228474	Gaussian
SSE Returns to GC & DXY Returns	0	GED
BSESN Returns to GC and DXY Volatility	0.079944	Gaussian
SSE Returns to GC & DXY Volatility	0	GED
BSESN Volatility to DXY & GC Returns	0.001946	GED
SSE Volatility to DXY & GC Returns	0	GED
BSESN Volatility to DXY & GC Volatility	0	GED
SSE Volatility to DXY & GC Volatility	0	GED
Normality Test Pre and Through-Pandemic (2020)	**Probability**	**Model**
BSESN Returns to GC and DXY returns	0.166108	Gaussian
SSE Returns to GC & DXY Returns	0	GED
BSESN Returns to GC and DXY Volatility	0.09344	Gaussian
SSE Returns to GC & DXY Volatility	0	GED
BSESN Volatility to DXY & GC Returns	0	GED
SSE Volatility to DXY & GC Returns	0	GED
BSESN Volatility to DXY & GC Volatility	0	GED
SSE Volatility to DXY & GC Volatility	0	GED

Analysis of GARCH results

The GARCH analysis results can be observed in tables 4 and 5 Where, the tables indicate the results that depict whether or not the independent variables GC and DXY returns and volatility have a significant effect on the dependent variables, i.e., the volatility of BSESN and SSE of the years 2019, 2020 and 2019 through 2020.

In the first GARCH results, as portrayed in table 4 can be observed that the only significant effect in the year 2019 is where DXY return negatively impacts SSE volatility. This proves that in the pre-pandemic era during the year 2019, H2a: US Dollar Index Negatively Impacts the SHANGHAI Stock Exchange Volatility is accepted since DXY returns do negatively affect SSE Volatility. Although it is to be noted that none of the GARCH probability is below the level of significance 0.05 (5%) thus, it does not follow the GARCH pattern.

In the year 2020, the rise of the epidemic BSESN volatility has been shown to be significantly affected by gold returns and volatility, since the gold returns have a significant negative effect H1b: Gold Price has a positive effect on BOMBAY Stock Exchange volatility is rejected.

SSE's volatility for the year 2020 has been positively affected by GC returns proving H1a: Gold Price has a positive effect on Shanghai Stock Exchange volatility to be accepted. In the case of DXY's effect on SSE's volatility in the pandemic era, it can be observed that DXY's returns negatively affect SSE volatility proving H2a (US Dollar Index Negatively Impacts the SHANGHAI Stock Exchange Volatility).

However, it is to be acknowledged that the effect of SSE's volatility does not follow the GARCH pattern as the Probability of GARCH for the volatility of SSE is well above the significance level of 0.05 (5%).

The GARCH analysis that was conducted on a combined data of two continues series of data being the year from the year 2019 through the year 2020, shows that GC and DXY returns have positively affected SSE volatility which approves H1a: Gold Price has a positive effect on SHANGHAI Stock Exchange volatility and disproves H2a: US Dollar Index Negatively Impacts the SHANGHAI Stock Exchange Volatility.

The result also shows that only the effect on the volatility of BSESN has a probability lower than the significance level of 0.1 (10%), which indicates that it follows the GARCH pattern. Nonetheless, the effect on SSE's volatility does not follow the GARCH pattern as the Probability of GARCH for the volatility of SSE is above the significance level.

Table 4.The Impact of Gold and DXY Return toward BSESN and SSE Volatility

Period	Dependent Variable	Independent Variable	z-statistic	Probability	GARCH	
					z-statistic	Probability
Pre-Pandemic	BSESN volatility	Gold Return	1.080345	0.28	0.218539	0.827
		DXY Return	0.957532	0.3383		
		C	72.46779	0.0000***		
	SSE Volatility	Gold Return	-1.292464	0.1962	-0.78474	0.4326
		DXY Return	-2.325786	0.0200**		
		C	81.08978	0.0000***		
Mid-Pandemic	BSESN Volatility	Gold Return	-2.037295	0.0416**	2.391041	0.0168**
		DXY Return	-0.231403	0.817		
		C	178.9479	0.0000***		
	SSE Volatility	Gold Return	2.860957	0.0307**	0.377822	0.7056
		DXY Return	-2.161154	0.0042***		
		C	76.77398	0.0000***		
Pre and Through Pandemic	BSESN volatility	Gold Return	-1.368658	0.1711	2.873163	0.0041***
		DXY Return	-0.1792	0.8578		
		C	328.6903	0.0000***		
	SSE Volatility	Gold Return	4.856326	0.0000***	-0.27036	0.7869
		DXY Return	8.039874	0.0000***		
		C	319.2561	0.0000***		

Note: *, **, *** indicates the level of significance at 10%, 5%, 1%

Table 5. The Impact of Gold and DXY Volatility toward BSESN and SSE Volatility

Period	Dependent Variable	Independent Variable	z-statistic	Probability	GARCH z-statistic	GARCH Probability
Pre-Pandemic	BSESN volatility	Gold Volatility	0.023424	0.9813	-1.29517	0.1953
		DXY Volatility	12.40282	0.0000***		
		C	-9.604537	0.0000***		
	SSE Volatility	Gold Volatility	-6319.956	0.0000***	0.275556	0.7829
		DXY Volatility	0.161808	0.8715		
		C	230,000,000	0.0000***		
Mid-Pandemic	BSESN Volatility	Gold Volatility	9.011802	0.0000***	2.151381	0.0314**
		DXY Volatility	2.093611	0.0363**		
		C	10.86821	0.0000***		
	SSE Volatility	Gold Volatility	2.825456	0.0047***	0.544944	0.5858
		DXY Volatility	8.670394	0.0000***		
		C	3.27325	0.0011***		
Pre and Through Pandemic	BSESN volatility	Gold Volatility	6.027007	0.0000***	1.90006	0.0574*
		DXY Volatility	-2.227655	0.0259**		
		C	56.82443	0.0000***		
	SSE Volatility	Gold Volatility	6.149309	0.0000***	-0.33752	0.7357
		DXY Volatility	3.810754	0.0001***		
		C	12.02436	0.0000***		

Note: *, **, *** indicates the level of significance at 10%, 5%, 1%

Table 5 indicating the second part of the GARCH analysis, which depicts the impact of the volatility of the independent data, as opposed to returns (Table 5), towards the dependent data. The effect that can be noticed is that the volatility of BSESN has been positively impacted by the volatility of DXY, which disproves the theory of H2a: US Dollar Index Negatively Impacts the SHANGHAI Stock Exchange Volatility. In comparison, the volatility of SSE has been negatively affected by GC volatility that disproves H1a (Gold has a positive effect on SHANGHAI Stock Exchange volatility). Although it is to be noted that for the year 2019, none of the GARCH probability is below the level of significance 0.05 (5%); thus, it does not follow the GARCH pattern.

It is depicted in table 5 that a significant effect seemed to be present in almost all scrutinized data. The year 2020's BSESN volatility has been significantly affected by gold volatility positively affecting it; hence, proving H1b acceptable. The volatility of BSESN has also been positively influenced by the volatility of DXY rejecting H2b: US Dollar Index Negatively Impacts the BOMBAY Stock Exchange Volatility.

Furthermore, SSE's volatility for the year 2020 has been positively affected by GC volatility, once again proving H1(a): Gold Price positively affects Shanghai Stock Exchange volatility to be accepted. DXY volatility has a positive effect on SSE volatility disproves the hypothesis H2a: US Dollar Index Negatively Impacts the SHANGHAI Stock Exchange Volatility. However, it is to be acknowledged that the effect of SSE's volatility does not follow the GARCH pattern as the Probability of GARCH for the volatility of SSE is above the level of significance 0.05 (5%).The final GARCH (Table 5) description on the combined data of two continuous series of data being drawn from the year (2019) prior to the novel coronavirus catastrophe combined with the data of year (2020) the epidemic broke out.

It can be noted from the results of the GARCH analysis that the volatility of the dependent variables has been mostly positively influenced. GC volatility has positively affected BSESN and SSE volatility (H1a and H1b accepted), while DXY volatility has negatively affected BSESN (H2b accepted), and positively affected SSE volatility (H2a rejected), respectively. The result also shows that only the effect on the volatility of BSESN has a probability lower than the significance level of 0.1 (10%), which indicates that it follows the GARCH pattern. Nonetheless, the effect on SSE's volatility does not follow the GARCH pattern as the Probability of GARCH for the volatility of SSE is above the significance level. In comparison, the GARCH model can be observed in the effect of BSESN volatility with the presence of a significance level below 10 percent (0.1).

5. DISCUSSION

In the study's first analysis of the volatile rate of the year 2019 and the year, before the novel pandemic struck, it seems to show that there was always a volatile presence of in relation to stock markets and the Gold Price and dollar index. As the GARCH analysis has proved in Table 5 that DXY volatility positively affects BSESN volatility, this proves that H2b is not accepted; this is in line with a study conducted by (Shafiullah et al., 2020). The literature proves a positive effect between the two variables; a rise in the US Dollar Price also causes an increase in the BRICS stock index and vice versa. Prior to the COVID-19 in the case of the SSE, the Dollar Index Returns (DXY) negatively impacts the stock market. Mikhaylov also proved this where the study proved that money markets, namely US Dollar, have a negative volatile spillover effect on emerging markets, thus proving hypothesis H2a as acceptable. The result also depicts so in the case with Gold Price (GC) Volatility, where the volatility of GC negatively impacts Shanghai Stock Exchange Volatility this portrays that in normal economic conditions, Chinese investors use gold as a hedging commodity for short term periods as they are more accustomed to responding to stock market news which tends to make them irrational traders as stated by He et al.,(2020). We can see that the majority of the stock market still had a negative impact on the emerging markets prior to the COVID-19 pandemic.

During the COVID-19 Pandemic, H1a has been accepted since gold price return and volatility seem to affect the Shanghai Stock Exchange positively. This is contradictory to previous year's findings. Implying that even though the COVID-19 pandemic existed, gold is and has been a long time safe-haven and hedge to most Chinese investors and the fact that the breakout of COVID-19 did have a major impact on several other financial markets; the Chinese investors reacted in a historic fashion by pursuing short-term security in commodity markets during the Covid-19 as a measure of flight-to-safety. However, considering the positive spillover effect from Gold to SSE Volatility proves that the measures taken by the Chinese government by imposing lockdowns to reduce the spread of the COVID-19 virus and other safety measures have seemed to benefit in recovery of the markets, this finding is also in line with Corbet et al., (2021). As there is no negative impact, it should translate that new investors looking to invest this as an opportunity to invest in relatively low-priced stocks in a bear-market economy. In the case of BSESN, gold volatility seems to have a positive effect, while Gold returns appear to have a negative effect. It has been studied by Reboredo (2012) when investigating gold's nature of safe haven that in terms of crisis, investors transfer from high-risk assets such as stock market into more reliable assets such as gold which in turn causes the stock markets to crash while appraising the price of gold due to increased demand. It appears that has also been the case during the COVID-19 pandemic, where investors are switching between assets to improve the effectiveness of their risk-return behavior. This conclusion is also on par with the results of Jain & Biswal (2016) as the GARCH results of Table 4 & 5 show a bilateral interrelation where the fall in Gold price leads to a fall in the Bombay Stock Exchange SENSEX and the fall in the SENSEX leading to an incrementation in Gold price.

Hypothesis 2a & 2b seem to be rejected in the case of the volatile independent data's effect towards both the dependent data. However, it can be observed in Table 4 that DXY Returns has a significant negative impact on SSE Volatility which approves H2a. This implicates that with the fall or rise of the Dollar Index, the SSE will face an opposite effect. However, this being said, the result is the same as the occurrences of the previous year, i.e., the pre-pandemic era, which shows that with or without the economic shocks, the US Dollar index's effect on Chinese financial markets remains unchanged. This could be due to the fact that the Chinese government, though they claim to be a managed floating regime, do intervene significantly in the exchange rate determination and also pose heavy regulation on everyday stock market price movement so as to shield their stock market from foreign capital movements causing high volatility in the Chinese financial markets (Naresh et al., 2018).

The overall analysis of the combined data of the years 2019 through 2020 shows that in all significant situations H1a and H1b is accepted where Gold Price return positively affects SSE volatility and Gold Price volatility positively affects SSE and BSESN volatility. This may not only be due to the fact that investors seeking safety during the 2020 crash turned to as a hedging mechanism, but could also is possibly due to the other fact that India and China are the world's highest consumers of gold not only as a commodity but also for cultural and traditional jewelry, ornaments, etc. On the other hand, DXY return and DXY volatility has had a significant positive effect on SSE volatility, completely disproving H2a while, DXY volatility has proved to negatively affect BSESN volatility proving H2b acceptable as India is a developing and emerging market whose financial markets are highly influenced by USD/IDR exchange rate unlike China, who is one of the world's leading economies and have high government intervention when concerning financial and economic factors.

6. CONCLUSION, LIMITATIONS, AND SUGGESTIONS

The research was done on this paper to prove that Dollar Index and Gold Price have had opposite effects on BSESN. This paper examined the role of GC and DXY in 2019 during the outbreak of the Coronavirus in 2019. The daily data of GC, DXY, and SESN served as independent variables to identify the significant influence studies report price volatility over time. The daily data was all used from January to August 2019 and August of 2020, as well as a merged daily series during these dates. The effects of Covid-19 ruled the stock markets since December 2019 and had already manifested in Chinese markets by February. This study, therefore, used data from January. Unit roots were first checked using the ADG methods, and no information was found, making the normality test applicable. Finally, the data was modeled using GARCH to calculate the amount of volatility

The study found that gold, ever since being used extensively as a hedge, trusted, and resorted to in both India and China, had a huge impact on the volatility of BSESN and SSE. While DXY, since it influences the USD/IDR Exchange Rate, did have a significant impact on BSESN. Although the significant impact of DXY towards SSE was very limited due to the strength of the Chinese economy, the rate at which the Chinese Yuan responds to the Dollar Index, and the heavy influence and intervention of the Chinese governments toward financial policies and prices. The intention of this study determines how the financial markets of China and India, namely, Shanghai Stock Exchange and Bombay Stock Exchange SENSEX, are volitively sensitive to two of the most major influencers of stock market spillover and trader mentality, i.e., Gold Price and the Dollar Index. Knowing these adverse effects can help government policymakers regulate or intervene to control extreme volatility, take timely action, and even prevent market crashes and negative spillover effects.

Even though this study proved the gap in the economic standing of both the emerging markets and how India is more vulnerable to the US Dollar rate and also how China, even though highly influenced by the pandemic, seemed to handle the after-effects of the shock relatively well, there are a few areas that are to be even more extensively studied to completely understand the investor behaviors and volatility spillover effects. Future researchers can also suggest that they also extensively include more independent variables such as Oil Prices, Exchange Rate/FOREX, and bitcoin, the latter especially in the case of China, as these variables play major roles in bear market situations also in cases of flight-to-safety and flight-to-quality.

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